A Mean Shift Clustering Based Segmentation of HR Satellite Imagery using Level set Approach

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***Abstract*: In this paper, a novel Fast Mean shift clustering for High Resolution (HR) satellite images with level set method. First we selectively penalize the level set function to be binary and then use a Gaussian smoothing kernel to regularize it. The advantages of our method is a new region based signed pressure force(SPF) function is proposed, which can step effectively the contour at weak or blurred edges and automatically detect the interior and exterior boundaries with the initial contour being any where in the images effected with noise. The proposed method allows a low dimensional image clustering with significant reduction of the complexity experimental results with High resolution satellite images show that the proposed algorithm is superior to the typical MS algorithm, producing high precision and requiring less operation time**.

Keywords- Active contours, Image segmentation, Chan-vase model, Level set method.

I. Introduction

Image Segmentation refers to the process of partitioning a digital image into multiple segments. It subdivides an image into it's constitute regions or object. The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Segmentation should stop when the object of interest in an application have been isolated. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Segmentation of nontrivial images is one of the most difficult tasks in image processing. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity or texture. Adjacent regions are significantly different with respect to the same characteristics [1-5].

Image segmentation plays an important role in the field of image understanding, image analysis and pattern identification. The foremost essential goal of the segmentation process is to partition an image into regions that are homogeneous (uniform) with respect to one or more

Self-characteristics and features. Active contour methods are applied in a wide range of problems including visual tracking and image segmentation. The basic idea is to allow a contour to deform so as to minimize a given energy functional in order to produce the desired segmentation. Two main categories exist for active contours: edge-based and region-based. Edge-based active contour models utilize image gradients in order to identify object boundaries, e.g., [6], [7]. Region- based ACMs have many advantages over edge-based ones. Initially, region-based models utilize the statistical information inside and outside the contour to control the evolution, which are less sensitive to noise; give better performance for images with weak edges or without edges and they are significantly less sensitive to the location of initial contour, further more they can efficiently detect the exterior and interior boundaries simultaneously.

In this paper, a novel mean shift clustering with level set method, i.e. Selective Binary and Gaussian Filtering Regularized Level Set Evolution (SBGFRLS), to implement our model. Unlike in Traditional Level Set methods, this method avoids the calculation of SDF and costly re-initialization [8-11].Firstly the Level Set Evolution will be penalized by using a selective step and then we use a Gaussian filter to regularize it. The Gaussian filter can make the level set function smooth and the evolution more stable. Furthermore, computational complexity analysis shows that the SBGFRLS method is more efficient than the traditional level set methods. In addition, the proposed model implemented with SBGFRLS has a property of selective global segmentation, which can not only extract the desired objects, but also accurately extract all the objects with interior and exterior boundaries[12-14].

This paper is organized as follows: In section II described the Mean shift clustering algorithm. In section III we describe our method with level set approach and show how to construct the region-based SPF function. Section IV validates our method by extensive experiments on HR satellite images.

II. MEAN SHIFT CLUSTERING APPROACH

A. *Intuitive Idea of Mean Shift:*

This section provides an intuitive idea of Mean shift and the later sections will expand the idea. Mean shift considers feature space as a empirical probability density function. If the input is a set of points then Mean shift considers them as sampled from the underlying probability density function. If dense regions (or clusters) are present in the feature space , then they correspond to the mode (or local maxima) of the probability density function. We can also identify clusters associated with the given mode using Mean Shift.

For each data point, Mean shift associates it with the nearby peak of the dataset's probability density function. For each data point, Mean shift defines a window around it and computes the mean of the data point . Then it shifts the center of the window to the mean and repeats the algorithm till it converges. After each iteration, we can consider that the window shifts to a denser region of the dataset.

At the high level, we can specify Mean Shift as follows:

1. Fix a window around each data point.
2. Compute the mean of data within the window.
3. Shift the window to the mean and repeat till convergence

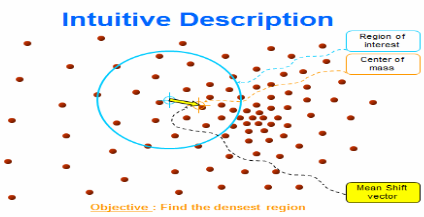

Fig.1: mean shift process

B. *Preliminaries:*

i. *Kernel Density Estimation*

Kernel density estimation is a non parametric way to estimate the density function of a random variable. This is usually called as the Parzen window technique. Given a kernel K, bandwidth parameter h , Kernel density estimator for a given set of d-dimensional points is

$$f(x)=\frac{1}{nh^d}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h}\right)\text{.........................}(1)$$

C. *Mean shift procedure:*

At density maxima $\nabla f(x)=0$

$$\nabla f(x)=\frac{2c_k}{nh^{(d+2)}}\sum_{i=1}^{n}(x-x_i)k'\left(\left\|\frac{x-x_i}{h}\right\|^2\right)$$

$$=$$

$$\frac{2c_k}{nh^{(d+2)}}\left(\sum_{i=1}^{n}g_i\right)\left(\frac{\sum_{i=1}^{n}x_i g_i}{\sum_{i=1}^{n}g_i}-x\right)\text{.....................}(2)$$

For

g(r)=k'(r), $g_i=g(\|(x-x_i)/h\|^2)$ ....(3)

As explained above, Mean shift treats the points the feature space as an probability density function .Dense regions in feature space corresponds to local maxima or modes. So for each data point, we perform gradient ascent on the local estimated density until convergence. The stationary points obtained via gradient ascent represent the modes of the density function. All points associated with the same stationary point belong to the same cluster

Mean Shift Vector:

$$m(x)=\frac{\sum_{i=1}^{n}x_i g_i}{\sum_{i=1}^{n}g_i}-x\text{............................}(4)$$

Successive locations of the kernel:

$$y_{j+1}=\sum_{i=1}^{n}x_i g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)\Big/\sum_{i=1}^{n}g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)\text{...........}(5)$$

D. *Algorithm Procedure for Mean Shift Clustering:*

Input : A positive integer k, n data points, , where i=1,2,……,n, one of the data points , and a total number N of iterations.

Output: An appropriate local maximum (mode) of the density

1. h=0.2
2. j=1
3. while j < N
4. $$y_2=\frac{\sum_{i=1}^{n}\frac{1}{h^{d+2}}x_i g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n}\frac{1}{h^{d+2}}g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)}$$
5. $y_1=y_2$
6. j =j+1
7. End while

III. LEVEL SET SEGMENTATION APPROACH

A. The Chan-Vese (Cv) Model:

Chan and Vese [15] proposed an ACM which can be seen as a special case of the Munford–Shah problem [11]]. For a given image I in domain X, the C–V model is formulated by minimizing the following energy functional:

$$E^{cv}=\lambda_1\int_{inside(c)}|I(x)-C_1|^2dx+\lambda_2\int_{outside(c)}|I(x)-C_2|^2dx, x\varepsilon\Omega \quad \ldots\ldots (6)$$

Where C1 and C2 are two constants which are the average intensities inside and outside the contour, respectively. With the level set method, we assume

$$C=\{x\in\Omega: \varphi(x)=0\}$$

$$\text{Inside}(C)=\{x\in\Omega: \varphi(x)>0\}$$

$$\text{Outside}(C)=\{x\in\Omega: \varphi(x)<0\}$$

By minimizing esq.: (1), we solve C1 and C2 as follows

$$C_1=\frac{\int_\Omega I(x).H(\phi)dx}{\int_\Omega H(\phi)dx} \quad \ldots\ldots\ldots\ldots(7)$$

$$C_2=\frac{\int_\Omega I(x).(1-H(\phi))dx}{\int_\Omega (1-H(\phi))dx} \quad \ldots\ldots\ldots(8)$$

By incorporating the length and area energy terms into Eq. (1) and minimizing them, we obtain the corresponding variational level set formulation as follows:

$$\frac{\partial\phi}{\partial t}=\partial(\phi)\left[\mu\nabla\left(\frac{\nabla\phi}{|\nabla\phi|}-\nu-\lambda_1(I-C_1)^2+\lambda_2(I-C_2)^2\right)\right] \quad \ldots\ldots (9)$$

Where $\mu\ \geq\ 0\ \nu \geq 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ are fixed parameters, μ controls the smoothness of zero level set, ν increases the propagation speed, λ_1 and λ_2 control the image data driven force inside and outside the contour, respectively. ∇ Is the gradient operator. $H(\phi)$ Is the Heaviside function and $\delta(\phi)$ is the Dirac function. Generally, the regularized versions are selected as follows:

$$H_\varepsilon(z)=\frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{z}{\varepsilon}\right)\right), \quad \ldots\ldots\ldots\ldots(10)$$

$$\delta_\varepsilon(z)=\frac{1}{\pi}.\frac{\varepsilon}{\varepsilon^2+z^2}, Z\varepsilon R$$

B. SPF function design:

The SPF function defined in [16] has values in the range [-1, 1]. It changes the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when outside the object, or expands when inside the object. Based on the analysis in Section 2, we construct the SPF function as follows:

$$spf(I(x))=\frac{I(x)-\frac{c_1+c_2}{2}}{\max\left(\left|I(x)-\frac{c_1+c_2}{2}\right|\right)}, x\varepsilon R \quad \ldots\ldots\ldots(11)$$

where C1 and C2 are defined in Eq. (7) and (8), respectively.

The significance of Eq. (11) is that, we assume the intensities inside and outside the object are homogeneous.} It is intuitive that $\min(I(x))\leq c_1,c_2\leq\max(I(x))$, and the equal signs cannot be obtained simultaneously wherever the contour is. Hence, there is

$$m\text{in}(I(x))\leq\frac{c_1+c_2}{2}\leq\max(I(x)), x\varepsilon\Omega \quad \ldots\ldots\ldots(12)$$

Obviously, the signs of the SPF function in Eq. (10) are identical; it can serve as an SPF function. Substituting the SPF function in Eq. (10) for GAC model, the level set formulation of the proposed model is as follows:

$$\frac{\partial\phi}{\partial t}=spf(I(x)).\left(div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+\alpha\right)|\nabla\phi|+\nabla spf(I(x)).\nabla\phi, x\varepsilon R \quad \ldots\ldots\ldots\ldots (13)$$

C. Implementation to level set:

In the traditional level set methods, the level set function is initialized to be an SDF to its interface in order to prevent it from being too steep or flat near its interface, and re-initialization is required in the evolution. The undesirable side effect in many existing re-initialization methods is moving the zero level set away from its interface. Furthermore, it is difficult to decide when and how to apply the re-initialization. In addition, re-initialization is a very expensive operation. To solve these problems, we propose a novel level set method, which utilizes a Gaussian filter to regularize the selective binary level set function after each iteration. The procedure of penalizing level set function to be binary is optional according to the desired property of evolution. If we want local segmentation property, the procedure is necessary; otherwise, it is unnecessary.

In our method, the level set function can be initialized to constants, which have different signs inside and outside the contour. This is very simple to implement in practice. In the traditional level set methods, the curvature-based term $div\left(\nabla\phi / |\nabla\phi|\right)|\nabla\phi|$ is usually used to regularize the level set function φ. Since φ is an SDF that satisfies $|\nabla\phi| - 1$ [17], the regularized term can be rewritten as $\Delta\phi$, which is the Laplacian of the level set function φ. As pointed out in [18-20] and based on the theory of scale-space the evolution of a function with its Laplacian is equivalent to a Gaussian kernel filtering the initial condition of the function. Thus we can use a Gaussian filtering process to further regularize the level set function The standard deviation of the Gaussian filter can control the regularization strength, just as the parameter μ in Eq. (4) does. Since we utilize a Gaussian filter to smooth the level set function to keep the interface regular, the regular term $div\left(\nabla\phi / |\nabla\phi|\right)|\nabla\phi|$ is unnecessary. In addition, the term $\nabla spf.\nabla\phi$ in Eq. (12) can also be removed, because our model utilizes the statistical information of regions, which has a larger capture range and capacity of anti-edge leakage. Finally, the level set formulation of the proposed model can be written as follows:

$$\frac{\partial\phi}{\partial t} = spf(I(x)).\alpha|\nabla\phi|, x\varepsilon\Omega \qquad \ldots\ldots\ldots (13)$$

The main procedures of the proposed algorithm are summarized as follows:Initialize the level set function Φ as

$$\phi(x, t=0) = \begin{cases} -\rho & x\varepsilon\Omega_0 - \partial\Omega_0 \\ 0 & x\varepsilon\partial\Omega_0 \\ \rho & x\varepsilon\Omega - \Omega_0 \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots(14)$$

1. Where $\rho > 0$ is a constant, Ω_0 is a subset in the image domain Ω and is the boundary of $\partial\Omega_0$ is the boundary of Ω_0.
2. Compute $c_1(\phi) and c_2(\phi)$ using Eqs. (7) and (8),
3. Evolve the level set function according to Eq. (13).
4. Let $\phi - 1$ if $\phi > 0$; otherwise, $\phi = -1$;

This step has the local segmentation property. If we want to selectively segment the desired objects, this step is necessary; otherwise, it is unnecessary.

5. Regularize the level set function with a Gaussian filter, i.e. $\phi = \phi * G_\sigma$
6. Check whether the evolution of the level set function has converged. If not, return to step 2.

IV. RESULTS AND DISCUSSIONS

Implementation of this model is done on two images of high resolution satellite images. The results are compared and analyzed with the previous work done. Original images are shown in first row and the second, third rows give the results of mean shift clustering segmentation image and the proposed MS clustering with level set method.

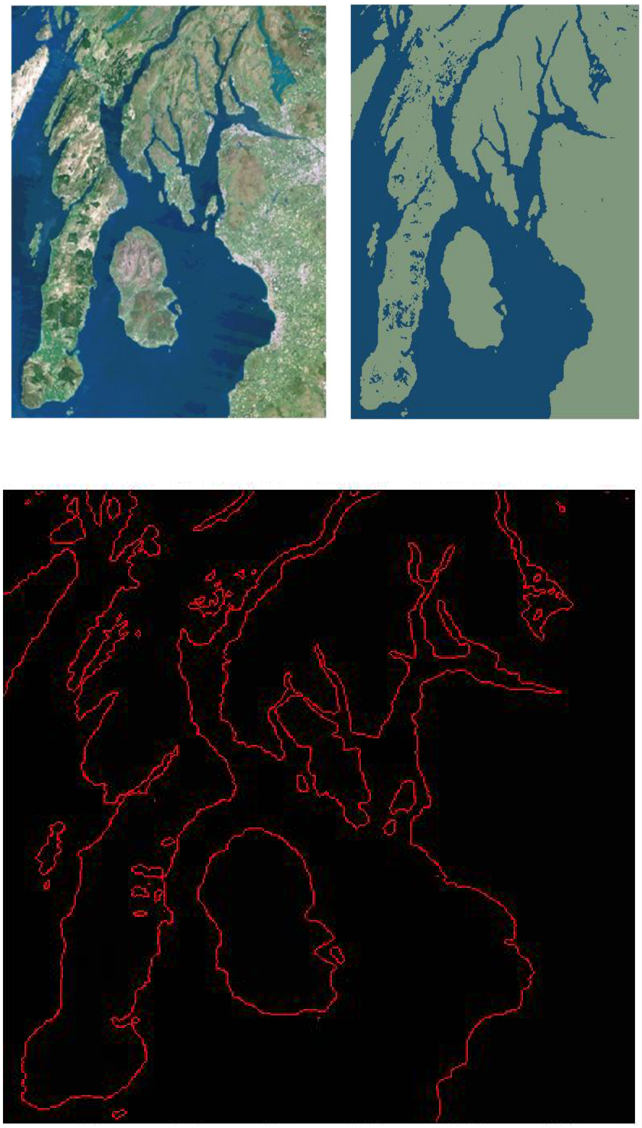

Fig 1: Results obtained with proposed method: column (a) is the original image, (b) is the mean shift clustered segmented image and the below column (c) represents the segmented image with MS clustered based level set method

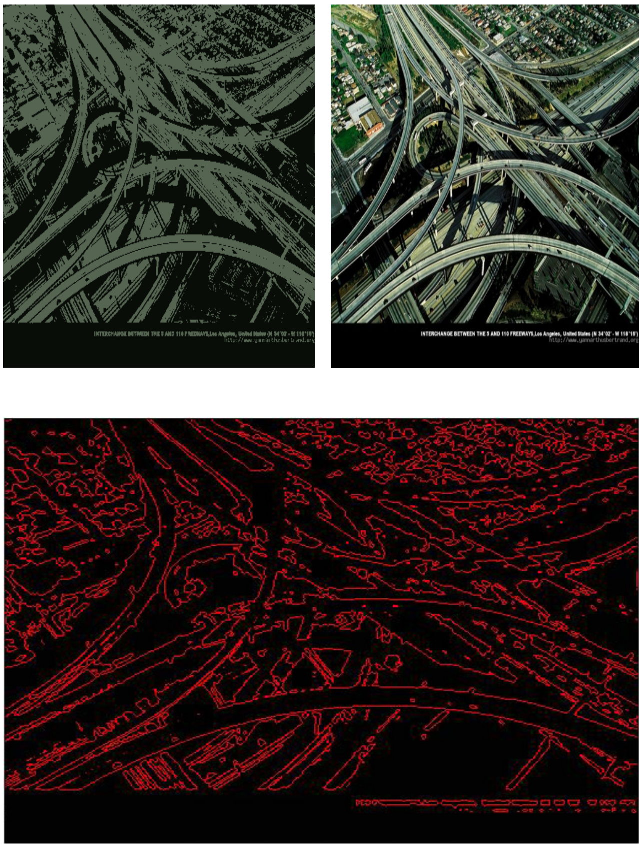

Fig 2: Results obtained with proposed method: column (a) is the original HR Satellite image, (b) is the mean shift clustered segmented image and the below column (c) represents the segmented image with MS clustered based level set method

Analysis Table:

Images	Proposed method			
	Iterations	evolution time	Parameter (mu)	Image Size
Image1	120	11.2934 sec	μ=55	340x400
Image2	120	12.6974sec	μ=60	375x500

V.CONCLUSION

In this paper, proposed a novel approach for Mean shift clustering with Level Set Evolution in satellite images. This image segmentation model has been successfully implemented on the high resolution satellite images and results reveal the speed, accuracy of high convergence and less number of iterations.

References

[1]. N. Xu, N. Ahuia, R. Bansal, Object segmentation using graph cuts based active contours, Computer Vision and Image Understanding 107 (2007) 210–224.

[2]. M. Kass, A. Witkin, D. Terzopoulos, Snakes: active contour models, International Journal of Computer Vision 1 (1988) 321–331.

[3]. T. Chan, L. Vese, Active contours without edges, IEEE Transaction on Image Processing 10 (2) (2001) 266–277.

[4]. V. Caselles, R. Kimmel, G. Sapiro, Geodesic active contours, in: Processing of IEEE International Conference on Computer Vision'95, Boston, MA, 1995, pp. 694–699.

[5]. V. Caselles, R. Kimmel, G. Sapiro, Geodesic active contours, International Journal of Computer Vision 22 (1) (1997) 61–79.

[6]. V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," *Int. Comput . Vis.*, vol. 22, no. 1, pp. 61–79, Feb. 1997.

[7]. C.Y. Xu, A. Yezzi Jr., J.L. Prince, On the relationship between parametric and geometric active contours, in: Processing of 34th Asilomar Conference on Signals Systems and Computers, 2000, pp. 483–489

[8]. Tsai, A. Yezzi, A.S. Willsky, Curve evolution plementation of the Mumford–Shah functional for image segmentation, denoising, interpolation, and magnification, IEEE Transaction on Image Processing 10 (2001) 1169– 1186

[9]. J. Lie, M. Lysaker, X.C. Tai, A binary level set model and some application to Munford–Shah image segmentation, IEEE Transaction on Image Processing 15 (2006) 1171–1181.

[10]. D. Mumford, J. Shah, Optimal approximation by piecewise smooth function and associated variational problems, Communication on Pure and Applied Mathematics 42 (1989) 577–685.

[11]. L.A. Vese, T.F. Chan, A multiphase level set framework for image segmentation using the Mumford–Shah model, International Journal of Computer Vision 50 (2002) 271–293.

[12]. R. Ronfard, Region-based strategies for active contour models, International Journal of Computer Vision 46 (2002) 223–247.

[13]. N. Paragios, R. Deriche, Geodesic active regions and level set methods for supervised texture segmentation, International Journal of Computer Vision 46 (2002) 223–247.

[14]. A. Blake and M. Isard, *Active Contours.*. Cambridge, MA: Springer, N. Paragios and R. Deriche, "Geodesic active contours and level for the detection and tracking of moving objects," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 3, pp 226–280, Mar. 2000.

[15]. T. Zhang and D. Freedman, "Tracking objects using density matching and shape priors," in *Proc. Int. Conf. Comput. is.*, 2004, pp.

[16]. N. Paragios, Y. Chen, and O. Faugeras, *Handbook of Mathematial Models in Computer Vision.*. New York: Springer, 2005.

[17]. O. Michailovich, Y. Rathi, and A. Tannenbaum, "Image segmentation using active contours driven by the bhattacharyya gradient flow," *IEEE Trans. Image Process.*, vol. 15, no. 11, pp. 2787–2801, Nov. 2007.

[18]. S. Osher, R. Fedkiw, Level Set Methods and Dynamic Implicit Surfaces, Springer-Verlag, New York, 2002.

[19]. C.M. Li, C. Kao, J. Gore, Z. Ding, Implicit active contours driven by local binary fitting energy, in: IEEE Conference on Computer Vision and Pattern Recognition, 2007

[20]. Li,C. Kao, J.C. Gore, Z. Ding, Minimization of region-scalable fitting energy for image segmentation, IEEE Transaction on Image Processing 17 (2008) 1940–1949.